

# **The Analysis of Multilevel Networks in Organizations: Models and Empirical Tests**

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### **Abstract**

Studies of social networks in organizations confront the analytical challenges posed by the multilevel effects of hierarchical relations between organizational sub-units on the presence or absence of informal network relations among organizational members. Conventional multilevel models may be usefully adopted to control for generic forms of non-independence between tie variables defined at multiple levels of analysis. Such models, however, are unable to identify the specific multilevel dependence mechanisms generating the observed network data. This is the basic difference between multilevel analysis of networks, and the analysis of multilevel networks. The aim of this paper is to show how recently derived Multilevel Exponential Random Graph Models (MERGMs) may be specified and estimated to address the problems posed by the analysis of multilevel networks in organizations. We illustrate our methodological proposal using data on hierarchical subordination and informal communication relations between top managers in a multiunit industrial group. We discuss the implications of our results in the broader context of current theories of organizations as connected multilevel systems.

**Keywords:** *Multilevel Exponential Random Graph Models, Multilevel Models, Multilevel Networks, Organizational networks, Social Networks.*

## Introduction

Research in organizational behavior (OB) has long been aware of the need to develop a multilevel understanding of individual behavior in organizations (Porter & Schneider, 2014). Somewhat more recently, a similar awareness also spilled over to neighboring research fields such as organizational psychology (Zohra & Luria, 2005), human resource management (HRM) (Wright & Boswell, 2002), organization and management theory (OMT) (Ibarra, Kilduff & Tsai, 2005), and management information systems (MIS) (McLaren, Head, Yuan, & Chan, 2011). Multilevel models are now common also in studies of leadership (Yammarino, Dionne, Chun, & Dansereau, 2005), and in research on human and social capital (Oh, Labianca & Chung, 2006; Ployhart & Moliterno, 2011). One consequence of these developments has been the progressive diffusion of multilevel research methods for studying organizations (Bliese, Chan & Ployhart, 2007; Klein & Kozlowski, 2000; Scherbaum & Ferreter, 2009).

Despite this extensive organizational literature, developing models capable of capturing multilevel network mechanisms has proved particularly elusive for social network researchers interested in examining “interpersonal networks within the larger contexts of organizations, looking at the effects of both interunit and interorganizational linkages” (Brass, Galskiewicz, Greve, & Tsai, 2004). This state of affairs is surprising given the considerable body of organizational research contributed by social network perspectives (Borgatti & Forster, 2003; Brass, Labianca, Mehra, Halgin, & Borgatti, 2014; Moliterno & Mahony, 2011). As Contractor, Wasserman, and Faust observe (2006: 684):

[O]ne of the key advantages of a network perspective is the ability to collect, collate, and study data at various levels of analysis (...). However, for the purposes of analyses most network data are either transformed to a single level of analysis (...) which necessarily loses some of the richness in the data, or are analyzed separately at different levels of analysis thus precluding direct comparisons of theoretical influences at different levels.

In an attempt to address this analytical concern, models for the analysis of multilevel networks have been recently proposed within the more general analytical framework of Exponential Random Graph Models (ERGMs) – a recently derived family of stochastic models for the analysis of tie variables at a single level of analysis (Snijders, Pattison, Robins, & Handcock, 2006). Multilevel Exponential Random Graph models (MERGMs) add the possibility of testing hypotheses about how the presence of network ties at one level (for example, between individuals) depend on the presence of ties at a higher level (for example, between organizational sub-units) (Wang, Robins, Pattison, & Lazega, 2013). This analytical framework would be clearly valuable in studying of organizations where “network nodes” (individuals) are typically contained in more aggregate structures (sub-units) which may themselves be connected through, for example, workflow or hierarchical relations.

Multilevel Exponential Random Graph models (MERGMs) have not been developed specifically for studying networks within organizations. While ERGMs are becoming more common in organizational research (Lomi, Lusher, Pattison, & Robins 2013), no empirical application is yet available where MERGMs are adopted for the analysis of social networks across multiple organizational levels. To the best of our knowledge, this article provides the first application of MERGMs to the analysis of intraorganizational relations.

We introduce MERGMs and illustrate how they may be useful to understand interpersonal networks of communication relations among the members of a top management team in a multiunit industrial group. In the empirical case study we present, subsidiary companies are the higher-level units. Members of the top management team are the lower-level units, or actors. We are interested in understanding the extent to which interpersonal communication networks crosscutting the boundaries of the subsidiaries (lower-level ties) are affected by hierarchical relations existing between the subsidiaries (higher-level ties). We clarify the

difference between multilevel analysis of social networks, and multilevel network analysis by providing a detailed guide to specification and empirical estimation of MERGMs.

Our more specific objective is to clarify the social and organizational mechanisms affecting the likelihood that informal communication networks will cross-cut the formal organizational boundaries encircling the subsidiary units. This objective is analytically important because research on social networks conducted at a single level is incapable of establishing the autonomy of informal boundary spanning ties with respect to formal relations existing between organizational units containing the individual network nodes. This objective is also substantively important given the far-reaching implications of boundary crossing ties for a variety of organizational outcomes (Hansen, 1999; Reagans & McEvily, 2003; Burt, 2004).

The article is organized as follows. In the next section, we outline the motivation for developing models for multilevel networks. In the third section, we introduce the MERGMs class of models, define their main analytical components, and state their main underlying assumptions. In the fourth section, we describe the research design behind our empirical illustration. We briefly discuss the variables, the measures needed for the specification of the empirical model, and the computational approach for estimating and evaluating MERGMs. In the fifth section we report the empirical estimates and provide an overall diagnostic evaluation of the model. We conclude with a short discussion on the general usefulness, applicability, and limitations of MERGMs in organizational research.

## **General Background and Motivation**

### *Multilevel models in organizations*

Organizations are a prototypical example of hierarchical multilevel social system (Kozlowski & Klein, 2000). Until relatively recent times, however, this observation has not been

accompanied by a parallel development of analytical approaches to the study of organizational behavior across multiple levels (Porter & Schneider, 2014). Thanks to advances in multilevel analysis, the situation is now rapidly changing within organization studies in general – and more specifically within the fields of organizational behavior, including leadership (Beal & Dawson, 2007; Bliese, Halverson, & Schriesheim, 2002; Hirst, Van Knippenberg, Chen, & Sacramento, 2011), human resource management (Bell, Tolwer, & Fisher, 2011), organizational communication (Monge & Contractor, 2003), and organization and management theory (Contractor et al., 2006).

In the typical organization, members are affiliated to internal units or work teams. Internal units and teams are part of companies. Companies (subsidiaries), in turn, may be contained in larger multiunit corporate formations (Granovetter, 2005; Hofmann, 1997). Group factors produced by common membership in superordinate units are important sources of non-independence in individual behavior. Because of the well-known statistical problems<sup>1</sup> caused by lack of independence in behavioral data, an increasing number of papers relies on multilevel modeling techniques to assess the influence of group factors on lower-level outcomes - typically on organizational members' attitudes and behaviors.

Multilevel models specify a set of lower- and higher-level actor covariates that are expected to explain lower-level outcome variables. In order to capture the total variance of the outcome variable(s), multilevel models estimate regression coefficients of lower-level variables and model between groups variation in an attempt to partial out the effect of the higher-level term (Hofmann, 1997). Various specifications have been introduced to deal with different data structures and research purposes (Bryk & Raudenbush, 1992; Hofmann, 1997). A number of methods have been proposed to alleviate issues of endogeneity - a central problem in assessing causality (Antonakis, Bendahan, Jacquart, & Lalive, 2010).

Multilevel modeling techniques have been successfully applied to a considerable variety of organizational phenomena. In studies of leadership, for example, multilevel models have been adopted to assess the effect of common group factors (e.g., complexity, professionalism and culture) on leadership emergence and performance (Mumford, Antes, Caughron & Friedrich, 2008). In the study of organizational socialization, team expectations and team performance have been shown to differently predict initial performance and performance improvement of newcomers (Chen, 2005). Despite these and related examples of successful organizational applications of multilevel models, the core insights of multilevel analysis does not extend directly to the analysis of multilevel networks. This is the main motivation for recent attempts to develop the specialized models for the analysis of multilevel networks that we discuss in this paper.

### *Networks in organizations*

Over the last two decades or so organizational and management research has emphasized the multiple roles that social networks play in organizations (Borgatti & Forster, 2003; Brass, Galskiewicz, Greve, & Tsai, 2004; Carpenter, Li, & Jiang, 2012). For example, research in organizational behavior instructs us that organizational members with high self-monitoring tendencies are more likely to occupy central positions in organizational networks (Mehra, Kilduff, & Brass, 2001), and that innovative ideas are more likely to originate with individuals occupying boundary spanning roles – or network positions connecting disjoint third parties (Burt, 2004).

More generally, the presence and absence of ties between organizational members has been shown to be systematically associated to important interpersonal differences in productivity (Reagans & Zuckerman, 2001), resources (Podolny & Baron, 1997), reputation (Kilduff & Krackhardt, 1994), propensity to innovate (Hansen, 1999), power (Brass & Burkhardt, 1993), and autonomy (Burt, 1992).

Networks exist at different organizational levels. Within organizations networks may be observed between individuals, units, teams, departments, or subsidiaries (Borgatti & Forster, 2003). Most available studies have analyzed these networks separately, typically ignoring the possible existence of dependencies across levels – multilevel network dependencies.

Because lower-level actors are nested in higher-level units (groups in standard multilevel modeling), relations between lower-level actors are nested in higher-level relations. Not surprisingly, awareness is increasing of the need to devote attention to antecedents and consequences of multilevel networks of this kind (Baum & Ingram, 2002; Brass, 2000; Brass et al., 2004; Oh, Labianca, & Chung, 2006).

Analyzing multilevel network systems involves specifying “how an observed network structure at one level of the system of organizational networks relates to network structures and effects at higher or lower levels of the system” (Moliterno & Mahony, 2011: 443). Building on this view, models for multilevel networks specify how relations between individuals in organizations are shaped by (1) their joint membership in more aggregate unit, and (2) the presence of relations between such units. Multilevel network models of this kind would have wide applicability.

Studies on leadership, for example, frequently apply a relational framework to identify emergent leaders, defined as organizational members recognized and nominated as leaders by their network peers (Balkundi & Kilduff, 2006). Similarly, studies of organizational reputation demonstrate that perceived network connections to prominent friends increase the reputation of individuals for high performance (Kilduff & Krackhardt, 1994). Despite the apparent validity of these results, a detailed analysis of the organizational setting would be needed to rule out the possibility that individual outcomes (like leadership or reputation) are a consequence of membership in units occupying a specific position in the network of formal hierarchical reporting relations, or in the workflow network. Without such assessment it may



be misleading to associate measures of leadership or reputation exclusively to personal characteristics or positions that individuals occupy in informal social networks within their units (Carson, Tesluk, & Marrone, 2007).

In summary, the multilevel character of interpersonal networks within organizations makes it necessary to develop a multilevel understanding of social networks, particularly – although not exclusively - when they are observed in intraorganizational contexts. Such understanding requires specification of specialized models for multilevel networks of the kind we illustrate in the empirical part of the paper. Before we do so, however, we need to clarify the fundamental differences between multilevel models for networks, and models for multilevel networks. The first class of models has found wide application in the study of organizational behavior (Rousseau, 1985) and consists of standard hierarchical linear models (HLMs) which specify relational characteristics of individuals –affiliated to different groups – within their own network (and, possibly, relational characteristics of groups) as predictors of individual behavior (Li, 2013). The second class of model is more recent and significantly less developed. We discuss this matter next.

#### *Models for multilevel networks in organizations*

The models for multilevel networks differ from standard multilevel models in at least two respects. First, multilevel network models take relations, rather than actors, as the focal element of analysis (Brass, 2000) - i.e., as the outcome variable. Network models are models for tie variables. Their main objective is to explain the presence or absence of ties between lower-level actors contained in more aggregate units that may themselves be connected. As such, network models are not general purpose models. They are useful only insofar one pursues specific analytical objectives requiring estimation of the probability of observing a tie between two nodes.

Second, multilevel network models are defined by hypothesis about dependence among tie variables specified at different levels of analysis. The predictors are local configurations of network ties (“network statistics”) defined across multiple levels (Wang, Robins, Pattison, & Lazega, 2013). The objective of multilevel network models is to assess the effect of higher-level predictors on the probability of observing a network tie, rather than estimating between group variation (Bryk & Raudenbush, 1992).

Because of these differences, standard multilevel statistical models (HLMs) apply only imperfectly to multilevel network problems. Available multilevel models can be adapted to social networks, because they can control for the effect of (lower- and higher-level) relational predictors like centrality measures on lower-level behaviors. This approach can successfully deal with endogeneity and other vexing statistical issues, as Li (2013) shows in a comprehensive review on regression methods applied to network data. However, conventional multilevel models typically adopted in the study of organizations would be of limited assistance in examining network dependences across levels as such models do not allow specification and identification of the form that such dependences might take.

With respect to multilevel issues, as Lazega, Jourda, Mounier, and Stofer (2008: 160) put it: “[A]lthough the multilevel dimension is intrinsic to the analysis of social networks, the analysis of relationship between structures of different levels remains underdeveloped.” Most of the empirical studies available have relied on various forms of simplification of the data structure in order to account for multi-level effects.

The typical approach consists in reducing a multilevel network to a single-level network, with a set of actors (individuals or units) and two relations among them, to then analyze the resulting network with standard social network analysis methods. Fernandez (1991), for example, in a study on emergent leadership, represents the formal hierarchical structure among divisions of a multiunit organization – which is an inherently interunit relation (Hansen, 1999)

– in a fine-grained way, as the “reporting to” relation among organizational members affiliated to the various divisions. He then analyzes this relation together with informal relation of “respect” and “friendship”. By contrast, Tsai (2002), in examining cooperation and competition within a multiunit organization, represents informal knowledge sharing as a relation between units and examines it together with formal cooperation ties. By assuming that relations are isomorphic across levels (Rousseau, 1985), this approach disregards the multilevel nature of the data structure. In doing so, this approach is likely to alter the relationships in the data and to increase the risk of misspecification or other statistical issues well documented in multilevel modeling (Hofmann, 1997; Rousseau, 1985).

### **Multilevel Exponential Random Graph Models**

#### *The Structure of Multilevel Networks*

Exponential Random Graph Models (ERGMs) are becoming increasingly common in studies of inter and intra-organizational relations (Lusher, Koskinen, & Robins, 2013). The ERGM framework allows investigating the development of networks and, mainly, structural ‘patterns and precursors of network formation’ (Carpenter et al., 2012: 1340). For instance, Srivastava and Banaji (2011) apply ERGMs to assess the association between self-related cognition and tendency to collaborate in a biotechnology company.

Multilevel Exponential Random Graph Models (or MERGMs – Wang, Robins, Pattison, & Lazega, 2013) are a new class of ERGMs specifically designed for the analysis of multilevel social networks. They are currently the only available method for the analysis of multilevel networks.

ERGMs – and MERGMs – have a common origin in logistic regression, but differ markedly from standard logistic regression techniques typically used to model network ties. While standard regression models require independence of observations, ERGMs are

designed for network data, whose observations (i.e., the ties) are linked by complex dependencies (Pattison & Robins, 2002). ERGMs provide a more direct methodological solution to the lack of independence problem that is unavoidable in network data (Snijders et al, 2006). The purpose of ERGMs is not to control endogenous dependence between tie variables but, rather, to model directly the underlying mechanisms responsible for producing dependencies among network ties.

### *Multilevel network data*

MERGMs have been derived for cross-sectional analysis. In their current version, MERGMs may be specified only for two-level networks. Like ERGMs, MERGMs are models for complete (rather than ego) networks (Lusher et al., 2013). The setting that is typically appropriate for an analysis of multilevel networks involves a multiunit organization whose members are affiliated to at least one unit - where units may be divisions, functions, work teams, projects or subsidiaries. Organizations are of different size. In published papers based on ERGMs, the number of network nodes ranges from very small – around 30 (Snijders et al., 2006) to fairly large – around 1700 (Goodreau, 2007).

Network relations of interest are defined among organizational members (henceforth, lower-level actors) and among the units (henceforth, higher-level actors). In the example that we present below, lower-level actors are managers of a multiunit organization, higher-level actors are the subsidiary units of the organization, network ties among lower-level actors are an informal communication relation on work-related matters, while network ties among higher-level actors are a hierarchical subordination relation.

Multilevel network analysis starts with the identification of a set of lower-level actors  $\mathbf{P}$  (for example, people), an affiliation set  $\mathbf{U}$  (for example organizational sub-units), and observations of network ties ( $\mathbf{R}$ ) within and between elements of these sets. Suppose that  $\mathbf{P}$  is the set of organizational members and that  $\mathbf{B}$  is a binary social relation defined between them

(where  $\mathbf{B}$  stands for relations defined between *lower-level* actors). Suppose, further, that  $\mathbf{U}$  is a set of organizational sub-units and that  $\mathbf{A}$  is a binary relation defined between them (where  $\mathbf{A}$  stands for relations defined between *higher-level* actors). Finally, suppose that  $\mathbf{X} (= \mathbf{P} \times \mathbf{U})$  is a bipartite binary association between elements of  $\mathbf{P}$  and elements in  $\mathbf{U}$  (where  $\mathbf{X}$  stands for relations defined between units *across different levels*). Then a multilevel network is simply a tuple  $\mathbf{M} = [\mathbf{P}, \mathbf{U}, \mathbf{B}, \mathbf{A}, \mathbf{X}]$ . To fix ideas, in the case study we develop in the empirical part of the study  $\mathbf{P}$  is the set of top managers in a multiunit group and  $\mathbf{B}$  is the network of informal communication observed between them.  $\mathbf{U}$  is the set of subsidiary companies to which the different managers are affiliated, and  $\mathbf{A}$  is a relation of hierarchical subordination defined between the subsidiaries. Finally,  $\mathbf{X}$  is a binary cross level relation affiliating managers to subsidiary companies.

In the empirical examples, we also collected data on attributes that may affect the likelihood of observing network relations within and across network levels.

**Figure 1** reports a network diagram of the data we analyze in the empirical part of the paper. Squares are subsidiary companies ( $\mathbf{U}$ ). Circles are managers ( $\mathbf{P}$ ). Dashed black ties are relations of hierarchical subordination between pairs of subsidiary companies ( $\mathbf{A}$ ). Solid black ties are informal communication relations between pairs of managers ( $\mathbf{B}$ ). An arrow signals the direction of the network tie. Grey links are affiliation ties of managers to subsidiaries ( $\mathbf{X}$ ).

--- Insert Figure 1 about here ---

### *Model Definition and Notation*

Assume that  $\mathbf{M}$  is a multilevel network consisting of  $i=1, \dots, j, \dots, v$  individuals ( $\mathbf{P}$ ) and  $l=1, \dots, k, \dots, u$  units ( $\mathbf{U}$ ).  $M_{ij}$  - the generic network tie between  $i$  and  $j$  – is conceived as a random variable with observed value  $m_{ij}$ .  $M_{ij}=1$  if there is a tie from  $i$  to  $j$  and  $M_{ij}=0$  otherwise.

MERGMs model the probability that a tie from  $i$  to  $j$  exists (so, a binary response variable) as a linear function – in logit form - of predictors. Each predictor corresponds to a network

configuration – i.e., a small subset of ties involving  $i$ , and capturing a social process going on around  $i$  and assumed to generate the predicted tie  $m_{ij}$ . Example of social processes is the tendency to reciprocate a tie and the corresponding configuration is a reciprocal tie  $(i,j)$  – i.e.,  $m_{ij}=m_{ji}=1$ .

The MERGMs formulation looks similar to binary logistic regression, with the main difference that the same tie is present on both sides of the equation and in multiple predictors<sup>2</sup>. Each configuration may be associated with a parameter that can then be estimated from data. This is a crucial difference between MERGMs and multilevel models with random or fixed effects which can control for generic forms of dependence, but cannot model them directly (Hofmann, 1997).

MERGMs may be specified as:

$$\Pr(M = m \mid Y = y) = \frac{1}{\kappa(\theta)} \exp \sum_Q \{a_Q z_Q^T(m) + \theta_Q z_Q^T(m, y)\} \quad (1)$$

where:

- $\mathbf{M}$  is the set of all possible multilevel networks of size  $(v \times u)$  and  $m$  is the observed network.  $\mathbf{M}$  can be thought of as the matrix of all the random variables  $M_{ij}$ , with observed value  $m$ .
- $\mathbf{Y}$  is a set of vectors of individual- and unit-specific characteristics and  $y$  is the observed set.
- $Q$  indicates the potential network configurations – as discussed in the next section (Robins, Elliott, & Pattison, 2001). The summation  $\Sigma$  is over all different configurations included in the model.
- $z_Q(m) = \sum_m \prod_{M_{ij} \in Q} m_{ij}$  are structural and  $z_Q(m, y) = \sum_m \prod_{M_{ij} \in Q} m_{ij} y_i$  are covariate network statistics corresponding to configuration  $Q$ . The statistics count, for each actor in the network, the number of configurations of each type in which the actor is involved – e.g., the number of reciprocal ties including actor  $i$ .

- $a_Q$  are structural and  $\theta_Q$  covariate parameters corresponding to configuration  $Q$ . A large and positive (negative) parameter estimate implies that the network contains more (less) configurations of that kind than those expected by chance. Given the tie dependence assumption, each parameter cannot be interpreted as an independent predictor, but is conceived as ‘conditional on the others’.
- $\kappa(\theta)_Q$  is a normalizing constant included to ensure that the sum of probabilities in (1) over all possible  $\mathbf{m}$  equals 1.

Equation (1) describes a general probability distribution of networks. It assumes that the probability of observing the empirical multilevel network structure depends on a small set of configurations, typically included according to theoretical assumptions on actor relational behavior in the context under examination<sup>3</sup> (Wang, Robins, Pattison, & Lazega, 2013).

We can express (1) also as the conditional log-odds (logit) of individual ties  $(i,j)$ :

$$\text{logit Pr}(M_{ij} = 1 \mid M_{hk} = m_{hk} \text{ for all } (h,k) \neq (i,j)) = \sum_Q a_Q \delta z_Q(m) \quad (2)$$

where  $\delta z_Q(m)$  is the amount by which  $z_Q(m)$  changes when  $M_{ij}$  is toggled from 0 to 1. If forming a tie increases the value of the statistic  $z_Q$  by 1, then, the log-odds of that tie forming increase by  $a_Q$  (or  $\theta_Q$ ) (Goodreau, Kitts, & Morris, 2009).

### *Network Configurations Within and Across Levels*

Structural configurations are a distinctive feature of ERGMs and consist of a small sub-set of ties (Snijders et al., 2006). The analytical objective of ERGMs is to estimate the incidence of these configurations on the probability of observing network ties between two nodes. These configurations represent the dependences between ties that standard statistical models usually ignore by either treating them as part of the error term (and then correcting generically the standard errors), or by including them as individual attributes – such as, for example, centrality, reciprocity, or brokerage measures (Li, 2013). None of these common model

building strategies can captures the underlying mechanisms of tie formation that ERGMs explicitly specify.

The vector of structural statistics  $z_Q(m)$  may include three level-related configurations:

- (a1) Lower-level configurations investigate relations within the lower-level network  $\mathbf{B}$ , i.e.,  $z_Q(b)$ , accounting for various characteristics of the interaction between individuals (Snijders et al., 2006). Published organization research based on ERGMs typically includes the specification of these configurations only (Srivastava & Banaji, 2011). The configurations used in the empirical exercise are reported in **Table 3**.

The higher-level configurations are the core part of MERGMs (Wang, Robins, Pattison, & Lazega, 2013). These configurations model relations between hierarchical levels and are:

- (a2) Configurations accounting for the group effect – i.e., the tendency of individuals assigned to the same unit(s) to interact with one another. Formally, these statistics link the network  $\mathbf{X}$  to the lower-level network  $\mathbf{B}$  - i.e.,  $z_Q(b, x)$ .
- (a3) Configurations “express[ing] tendencies for structural [configurations] to be associated across both levels simultaneously” (Wang, Robins, Pattison, & Lazega, 2013: 99). These configurations involve all the three networks – i.e.,  $z_Q(a, x, b)$  are labelled as ‘cross-level’ because include both lower-level and higher-level ties. These configurations allow probabilistic assessment of whether the position of organizational members in the interpersonal network or the ties between organizational members may be linked to the position of their units in the interunit network or to the ties between units.

The higher-level configurations used in the empirical exercise are reported in **Table 4**.

Covariate configurations include actor characteristics (Robins et al., 2001; Wang, Robins, Pattison, Lazega, & Jourda, 2013), specified as attributes of each actor or similarities between pairs of connected actors. Similarly to the vector of structural configurations, the vector of covariate configurations  $z_Q(m, y)$  includes:



- (b1) Configurations accounting for the influence of individual ( $y^B$ ) attributes on interaction in network  $\mathbf{B}$ , i.e.,  $z_Q(b, y^B)$ . These configurations may be specified to test whether individuals are more likely to interact with others if they have some attributes or are similar to others in some attributes.
- (b2) Configurations accounting for the interdependence between lower-level and affiliation networks, i.e.,  $z_Q(b, x, y^B)$ . These configurations may be specified to test whether individuals assigned to the same unit are more likely to interact with one another if they have or are similar in some attributes.
- (b3) Configurations accounting for the influence of unit or individual attributes on the dependence of lower-level ties on interunit ties, i.e.,  $z_Q(a, b, x, y^A, y^B)$ . These configurations may be specified to test whether the association between interpersonal and interunit ties mentioned above are more likely when individuals or units have some attributes or are similar respectively to other individuals/units in some attributes.

The lower- and higher-level covariate configurations used in the empirical exercise are reported in **Table 5**.

### **Empirical Illustration**

In the next section we situate the model just discussed in the context of an analysis of knowledge sharing in a multiunit industrial company with five organizational units (subsidiary units or subsidiaries from now on). This organizational setting provides ideal testing grounds for the analysis of multilevel networks because: (a) subsidiaries are designed to be repositories of specialized knowledge; (b) individuals across subsidiaries establish informal networks of communication relations to mobilize knowledge resources across organizational boundaries and have access to diversified knowledge; and (c) subsidiaries are connected by hierarchical reporting relations, which represent the formal organizational structure (Argote, McEvily, & Reagans, 2003; Tushman, 1977).

The main goal of the analysis is to assess how the formal organizational structure sustains (or constrains) information sharing across organizational boundaries. More specifically we ask: How autonomous are boundary spanning ties? In other words, does informal interpersonal interaction span subsidiary boundaries *independent of* the formal hierarchy of relations existing between subsidiaries? Does the position (and, therefore, the role) of a subsidiary within the formal organizational structure make its members particularly active or attractive in informal interaction and, thus, contribute to explain individuals' position (and role) in information sharing? Finally, how do patterns of hierarchical relations linking the subsidiaries affect interpersonal interaction? These questions are at the heart of current research investigating the coupling/decoupling of formal and informal relations (McEvily, Soda, & Tortoriello, 2014; Kleinbaum, Stuart, & Tushman, 2013) and trying to link properties of social networks to relevant organizational outcomes like innovation and performance (Burt, 2004; Dokko, Kane, & Tortoriello, 2014; Tsai, 2001). As we demonstrate in the empirical example that we present next, these questions can be answered convincingly only by assuming - and then testing - specific forms of multilevel network relations linking individuals, organizational units, and individuals and organizational units.

## **Research design**

### *Data*

We studied an international multiunit industrial group active in the design, manufacturing and sale of leisure motor yachts. The group consists of subsidiary units, and each organizational member is unambiguously and uniquely assigned to one subsidiary. Since the subsidiaries act as quasi-independent companies and occupy different market niches, coordination and collaboration across the boundaries of subsidiaries are crucial, especially for members working in the same functional areas. Boundary-spanning interaction would

allow members to share information on technical solutions, potential customers or competitors, and is, therefore, highly encouraged.

We examined informal relations of interpersonal communication among the forty-seven members of the group top-management team ( $\mathbf{P}$ ).<sup>4</sup> Each participant was administered a questionnaire, containing the list of names of the other 46 managers, and was asked to report the presence of personal communication ties (McCulloh, Armstrong, & Johnson, 2013). The question was framed in terms of advice – at least on a daily frequency - on work-related matters (such as information about dealers, competitors, production delays). We obtained a 100% response rate. We arranged the data in matrix  $\mathbf{B}$  ( $47 \times 47$ ): the generic cell  $b_{ij} = 1$  if manager  $i$  communicates with manager  $j$  on work-related matters on a daily basis at least.

Hierarchical relations between subsidiaries ( $\mathbf{U}$ ) were reconstructed by asking the corporate CEO to indicate “who reports to whom.” We provided him with the names of the 47 participants arranged in the rows and in the columns of a square matrix. We asked him to indicate whenever the column person reported to the row person. For example, if the “Chief engineer” (column)  $j$  in subsidiary  $k$  reported to the “Chief Corporate Engineer” (row)  $i$  in subsidiary  $l$  then  $a_{ij} = 1$ . In this case  $i$  would be hierarchically superordinate to  $j$  ( $i \rightarrow j$ ). We arranged these data into the matrix between the subsidiaries<sup>5</sup>,  $\mathbf{A}$  ( $6 \times 6$ ): the generic cell  $a_{lk} = 1$  if subsidiary  $l$  is hierarchically superordinate to subsidiary  $k$ , i.e., if there is at least one manager  $j$  in  $k$  reporting to a manager  $i$  in  $l$ .

We linked managers to subsidiaries in the (managers-by- subsidiary) matrix of containment relations  $\mathbf{X}$  ( $47 \times 6$ ): the generic cell  $x_{il} = 1$  if manager  $i$  belongs to subsidiary  $l$ .

Finally, we used  $\mathbf{B}$ ,  $\mathbf{A}$  and  $\mathbf{X}$  to build  $\mathbf{M}=[\mathbf{P}, \mathbf{U}, \mathbf{A}, \mathbf{B}, \mathbf{X}]$ .

--- Insert Table 1 about here ---

A different section of the questionnaire was designed to elicit demographic and organizational information that was used to construct the control variables included in our

empirical model specifications. **Table 1** and **Table 2** report the basic descriptive statistics computed respectively for the interpersonal network and for the control variables.

--- Insert Table 2 about here ---

### *Empirical Model Specification*

To model interpersonal interaction, we specify a set of configurations that, according to theory, are likely to shape a communication network (class (a1) displayed in **Table 3**).

*Density* accounts for the general propensity of managers toward communicating with others. Because building and maintaining many relations is costly, this tendency is usually negative. *Reciprocity* tests the likelihood that two managers reciprocate relations, exchanging information with one another. *Popularity spread* examines the likelihood that few managers are particularly popular – i.e., are chosen as communication partners and receive diversified information from many others. *Activity spread* accounts for the tendency of managers to be particularly active – i.e., to communicate with many others, contributing to information spreading.

*Closure* configurations test the propensity of managers to form sub-groups (Snijders et al., 2006) and are generally associated to redundant information. *Transitive closure* implies that managers are more likely to communicate with colleagues if they share multiple communication partners. *Cyclic closure* tests whether information sharing occurs within sub-groups without any expectation of being reciprocated. Finally, *2-paths* tests the likelihood that the same managers are sought and seek colleagues as communication partners. Since these individuals would connect those from whom they receive information to those to whom they give information, *2-paths* could be interpreted as tendency against forming sub-groups.

--- Insert Table 3 about here ---

Structural higher-level configurations (**Table 4**) are the focus of multilevel modeling exercises. *Affiliation based closure* – (a2) in the list above – tests whether managers are more likely to talk to colleagues affiliated to the same subsidiary - i.e., propensity against boundary spanning.

*Cross-level assortativity* statistics – class (a3) – test the tendency of managers active/popular in the communication network to be affiliated to active/popular subsidiaries in the hierarchical network. *Cross-level in-degree assortativity* tests whether managers sought as communication partners by many colleagues are likely to be affiliated to subsidiaries receiving many ties in the formal organizational network - i.e., hierarchically subordinate subsidiaries. *Cross-level out-degree assortativity* accounts for the opposite effect – i.e., the likelihood that managers sharing information with many colleagues are affiliated to subsidiaries, to which many others have to report (i.e., hierarchically superordinate).

*Cross-level alignment* configurations – class (a3) – account for the propensity of members of different subsidiaries to talk to each other if their subsidiaries are connected. Hence, these configurations capture the likelihood that informal ties spanning boundaries defined around subsidiaries are sustained by formal organizational ties. *Cross-level alignment entrainment* implies that interpersonal ties follow the hierarchical ordering imposed by the formal structure, thus controlling for a tight coupling between formal and informal relations (McEvily et al., 2014). Managers are likely to talk to colleagues affiliated to subsidiaries that are hierarchically dependent on their own subsidiary. The *exchange* version controls for a loose coupling and can be interpreted as managers' propensity toward inverting the hierarchy, building communication ties with colleagues affiliated to hierarchically superordinate subsidiaries. The *exchange reciprocal B* configuration accounts for managers' likelihood to reduce the hierarchical distance building reciprocal ties with colleagues affiliated to subsidiaries with which a hierarchical link exists.

--- Insert Table 4 about here ---

Finally, we specify a set of covariate configurations (see **Table 5**). For interpersonal communication, we include the *Covariate match* statistic – class (b1) –. It tests whether managers are more likely to communicate with colleagues similar to them with respect to various personal (gender, nationality) and work-related (function, company grade and tenure) attributes.

The covariate matching process is also investigated for multilevel dependences – class (b3) –. *Cross-level alignment individual covariate match* enters the model as *entrainment*, *exchange* and *exchange reciprocal B* configurations for individual grade and membership in organizational function. These configurations verify whether various types of association between lower- and higher-level ties are more likely when managers are similar in respect to the specified attribute.

Finally, we specify *Cross-level alignment entrainment* and *Cross-level alignment exchange unit covariate match* also for subsidiaries' country, role and size.

--- Insert Table 5 about here ---

### *Model Estimation and Evaluation*

To account for the dependence between ties, the estimation of MERGMs parameters relies on Monte Carlo Markov Chain Maximum Likelihood (MCMCML) or related simulation-based techniques (Hunter & Handcock, 2006; Snijders, 2002).

The observed network  $\mathbf{m}$  is assumed as a single observation of a distribution of random networks  $\mathbf{M}$  with the same number of actors of  $\mathbf{m}$ , i.e.  $(v \times u)$ . In the case study, for example, the number of lower-level actors ( $v$ ) is 47, the number of higher-level actors ( $u$ ) is 6, and the set of possible networks is  $(u \times (u-1) \times u \times v \times v \times (v-1))=18,290,520$ . Each network is assigned a probability of occurrence, depending on the model predictors and related parameters. Hence, the range of possible networks and their probability of realization under

the model are represented by a probability distribution. The networks that most resemble the observed network have a higher probability of occurrence. The estimation process uses the observed network as a guide and consists in selecting parameter values that reproduce the observed network well, applying a maximum likelihood estimation criterion. To progressively approximate the likelihood and refine the parameter estimates, a number of networks are sampled from the space of possible networks of size  $(v \times u)$ , using the probability distribution (with the initial parameter estimates), and, then, compared to the observed network. The process is repeated until the estimates stabilize (Robins, Snijders, Wang, Handcock, & Pattison, 2007).

The simulated networks are used also to evaluate the goodness of fit of the model. The distribution of graphs implied by the model is simulated using the parameter estimates. For each included configuration, this distribution of graphs will necessarily be consistent with the observed graph. For other network features, the goodness of fit is assessed by comparing the observed values to the estimated distribution of that feature implied by the model itself (Goodreau, 2007; Hunter, Goodreau, & Handcock, 2008). The first type of features are MERGMs configurations not included in the model, which are tested in order to verify whether the set of included statistics suffices to explain which tendencies shape the network. The second type involves structural properties of the observed graph – e.g., various aspects of the degree distributions -, which are tested to verify whether the estimated configurations are capable of reproducing the overall observed network structure. A *t-ratio* is used to assess model fit. This *t-ratio* is computed as the difference between the observed statistic and the mean statistic from the simulated networks, divided by the standard deviation. As a rule of thumb (Hunter et al., 2008; Robins & Lusher, 2013), an absolute value of the *t-ratio* close to zero, or at least smaller than 2, indicates that the model reproduces the corresponding statistic well.

Estimates and goodness of fit diagnostics are produced using the software MPNet (Wang, Robins, Pattison, & Lazega, 2013), a freely available software specifically designed for MERGMs (see the appendix for details).

## Analysis

### *Results*

**Table 6** reports estimates and associated standard errors of the model parameters. Similarly to a logistic regression model, the estimates may be interpreted as conditional log-odds for the presence of tie.

--- Insert Table 6 about here ---

We specify three models ordered in terms of increasing complexity. Model 1 is a baseline or tie independent model, similar to logistic regression. This model includes the intercept (i.e., *Density*) and the covariate configurations for the interpersonal network, assuming that the likelihood of observing ties is explained by individual characteristics only. Model 2 is the single-level network model. It includes structural and covariate configurations for the interpersonal network. Model 2 allows us to introduce the general ERGMs framework and to comment on conclusions that could be drawn from analyzing informal interpersonal communication only, ignoring the hierarchical relations between the subsidiaries. Model 3 is the multilevel network model. It includes multilevel configurations and examines the dependence between formal inter-subsidiary ties and informal interaction. Since Model 3 is our full model, we comment on this, highlighting the differences with Model 1 and 2.

Accounting for higher-level configurations (Model 3) modifies the values of many lower-order parameters and increases the values of the corresponding standard errors. Like in standard regression, multilevel modeling allows better assessing the predictors' variation (Bryk & Raudenbush, 1992).



The *Density* parameter is negative, as it is typically the case in empirical networks, to indicate that communication ties are costly to establish. This tendency is much stronger in Model 3 than in Model 2 and 1 (respectively -7.52, -3.41 and -2.31)<sup>6</sup>. Once we account for the formal structure, there is almost no chance of observing “random” communication ties - i.e., ties that are not part of more complex network sub-structures.

The significantly positive value of the *Reciprocity* parameter (3.13 in Model 2 and 2.62 in Model 3) indicates that managers are likely to build mutual ties and to share information on a not hierarchical basis. This propensity, however, decreases in magnitude<sup>7</sup> from Model 2 to Model 3. The positive effect of *Activity spread* (0.50) suggests the presence of a restricted number of managers particularly active in communicating with many colleagues.<sup>8</sup> These managers rely on many others as sources of information and are likely to diversify their range of available knowledge. The combination of a positive *Transitive closure* – decreasing from Model 2 to Model 3 - (1.28 and 0.79 respectively) and a negative, although not significant, *Cyclic closure* parameter (-0.16), indicates that managers tend to interact in small sub-groups. Akin to a bonding social capital perspective, the available information are likely to be redundant and their spread controlled by few members of the sub-groups. The significantly negative *2-paths* (-0.19) enforces this result, outlining that managers are unlikely to spread information across different groups. Since *2-paths* indicates also that the same individuals receive and share information, the negative parameter suggests the existence of a division of roles.

The parameters of several higher-level configurations are significant, indicating an association between information sharing among managers and the hierarchical structure, and suggesting how this association takes place.

The significantly positive *Affiliation based closure* parameter (2.74) indicates that managers are likely to communicate with colleagues in the same subsidiary. This result

captures the well-known tendency of organizational unit boundaries to restrict the range of relations and information available for managers (Reagans & McEvily, 2003). The significantly positive *Cross-level in-degree assortativity* parameter (1.17) suggests that managers more sought after by colleagues as communication partners are affiliated to subsidiaries which have to report to several others - i.e., hierarchically subordinate. Hence, information are likely to flow from members of subordinate to members of superordinate units. The positive *Cross-level alignment exchange reciprocal B* (2.14) outlines that managers are likely to build mutual relations to others with different affiliation and hierarchical level. The managers span their unit boundaries in sharing information when the interpersonal ties are sustained by hierarchical dependence ties between the subsidiaries. The formal interunit relation provides managers with opportunity to meet and share information (Kleinbaum et al., 2013). Combined with the statistically non-significant *Cross-level alignment entrainment* and *exchange* parameters, the *Cross-level alignment exchange reciprocal B* emphasizes the importance of mutual relations as a key driver of boundary spanning.

The significance of the individual covariates changes across model specifications. The *Grade* and *Tenure match* configurations are significant in the first two models, but disappear in Model 3. When we ignore the higher-level network, we find that managers are likely to interact with colleagues similar in terms of status (as measured by job grade), and experience (as measured by tenure).

When the organizational hierarchical structure is accounted for (Model 3), these individual characteristics no longer have a significant effect on the presence of communication ties between individuals. In Model 3 homophily seems to operate only through organizational structure. Contrary to the tendency illustrated above, the positive *Cross-level alignment entrainment function match* (2.12) suggests that managers in the same functional area tend to

talk to colleagues affiliated to subsidiaries that hierarchically depend on their own subsidiary. Membership in the same professional function encourages the establishment of boundary spanning ties that preserve the hierarchical ordering. This effect of inter-subsi-diary hierarchy within the same functional area is confirmed by the negative *Cross-level alignment exchange reciprocal B function match* parameter (-4.31).

### *Model Evaluation*

We conclude our analysis by testing the ability of the estimated models to reproduce salient characteristics of the observed network as a whole. We find that this ability is significantly higher for the multilevel network model.

We follow recommended best practices in the analysis of ERGMs (Hunter et al., 2008) and produce a sample of 1,000 graphs drawn from the random graph distribution simulated based on the empirical estimates. We extract these graphs from a simulated distribution of graphs after 1,000,000 iterations, and after a 100,000-iteration burn-in phase. Since both networks *X* and *A* are considered exogenous in the estimation process, the goodness of fit check focuses on the interpersonal network.

As we discussed, any feature of interest in the observed graph can be compared to the distribution of such features in the model. We use the *t-ratio* to detect the location of the observed feature in this distribution. Values larger than 2 in absolute value suggest that the observed graph differs from the distribution implied by the model in the corresponding feature (Hunter et al., 2008). Hence, the model is not capable of capturing the feature. **Table 7** reports comparisons for a variety of crucial characteristics: features of the distributions of incoming and outgoing ties as well as a set of coefficients controlling for the existence of connected sub-groups – clustering coefficients, i.e., GCC (Luce & Perry, 1949). The values show that the multilevel network model (Model 3) captures much better than the others these features of the observed networks.

--- Insert Table 7 about here ---

In detail, for Model 1 three of the six *t-ratio* values reported in **Table 7** are significantly larger than the threshold 2 in absolute magnitude. It outlines that it not possible to reproduce the network features well without accounting for the local dependence structures implied by ERGMs. Hence, this result points to the usefulness of the ERGMs framework. For Models 2 and 3 all the *t-ratio* values are significantly smaller than the threshold. Indeed, Model 3 provides much more accurate estimates of all the network characteristics, as most of them become closer to zero.

We investigate goodness of fit also on the set of MERGMs configurations not parameterized in the estimated models. These configurations are all the structural and covariate statistics that can be included to modeling the interpersonal network as well as the interaction across levels. Also in this case, we find that Model 3 ensures a significant improvement in the fit for the most statistics: it reproduces 97 out of the 99 statistics that can be specified. Models 1 and 2 have a considerably poorer fit: they reproduce only 44 and 64 statistics, respectively.

## Conclusions

In this paper we have presented newly derived Multilevel Exponential Random Graph Models (MERGMs) for the analysis of multilevel networks in organizations (Wang, Robins, Pattison, & Lazega, 2013). More specifically, we have (i) framed MERGMs as one feasible analytical strategy to represent multilevel mechanisms of network tie formation; (ii) illustrated the distinctive analytical insights that these models provide on the multilevel dependencies inherent in social networks within organizations, and (iii) discussed how such insights may contribute to a more detailed understanding of the relations between formal structure and informal networks in organizations (McEvily et al., 2014).

We have emphasized the specification and estimation of parameters corresponding to local configurations of network ties across levels. MERGMs are the only models that afford direct estimation of such parameters. This emphasis clearly marks the fundamental difference between the class of *multilevel models* for social networks (Li, 2013), and the class of *multilevel social network models* that MERGMs represent. *Multilevel models* for networks can *control* for network dependencies in observations across levels, but they offer only limited assistance in developing and testing hypothesis about the specific forms that multilevel dependences might take in any specific data set. The main analytical objective of *multilevel network models* is to represent these dependencies directly and explicitly.

We have illustrated the empirical value of MERGMs examining information sharing relations among members of the top management team within a multiunit organization. Using data we have collected on relations of hierarchical subordination and informal communication between the managers, we have shown how MERGMs may be specified to address a number of core concerns in multilevel organizational analysis. We focused our discussion on the tendency of informal information sharing relations to cross-cut the formal sub-unit boundaries. We have documented specific ways in which boundary crossing ties are sustained by hierarchical organizational structure (Reagans & McEvily, 2003).

We have shown, further, that multilevel network models take us beyond the empirical regularities documented in received organization research. We have indicated various ways in which ties between subsidiaries can affect interpersonal sharing of information. In doing so, we have suggested that well-known properties of informal social networks (i.e., actor centrality, reciprocity of ties) may actually depend on the properties of the settings in which interaction occurs – and not just on the characteristics of the individuals involved in interaction. We reported results showing that the most popular managers in the communication network are member in the most popular subsidiaries. This seems to be

particularly salient in our study because suggests that “centrality” – one of the most common network measures used in empirical studies of organizational behavior (Brass & Burkhardt, 1992), leadership (Balkundi & Kilduff, 2006) and human resources management (Sparrowe, Liden, Wayne, & Kraimer, 2001) – comes also from membership in central subsidiaries, rather than individual attributes or even network positions. If replicated, this result might lead to a systematic re-evaluation of the meaning and causal standing of centrality and other popular network constructs that are extensively used in organizational research.

We have shown, finally, that boundary-spanning ties tend to be supported by – and co-occur with formal relations between the subsidiaries. Managers in different subsidiaries are unlikely to entertain informal relations with one another unless the subsidiaries are themselves connected. When supported by formal ties, informal ties between managers are characterized by significant tendencies toward reciprocity. This is, therefore, the key mechanism that allows informal interaction to span formal boundaries.

In closing, it seems appropriate to acknowledge the main limitations of the modeling approach that we have proposed. These limitations suggest caution in the interpretation of the results we have reported, but also indicate clear directions for future research. First, MERGMs are not general-purpose regression-like models. They are a specialized class of models developed for assessing dependences between binary tie variables. They are valuable only to the extent that the issue being addressed requires explicit modeling of the mechanisms generating dependences between network ties. The relatively limited range of data structures that may be used to estimate MERGMs is compensated, in part, by the unique possibility afforded by MERGMs to model explicitly endogenous tie dependence mechanisms that in more established hierarchical linear models can only be corrected for generically. To broaden the appeal and applicability of MERGMs, future research will have to extend the basic setup that we have described in this paper to more general and flexible data structures.

Second, MERGMs share most of the limitations of the ERGM class of models from which they derive. The main of such limitations is probably that MERGMs are models for cross-sectional data. This limits our understanding of the specific mechanisms underlying the formation and change of network structures in organizations. At best, estimated values of MERGM parameters represent cross-sectional traces of causal mechanisms that may be at work to produce the observations. The cross-sectional nature of MERGMs also limits our ability to tease out the separate effects on the formation of network ties of individual (exogenous) characteristics of the “nodes” (people in our case), and the endogenously determined positions they occupy in the network of social and communication relations. Stochastic actor-oriented models for dynamic multilevel networks are probably more useful to address such questions (Snijders, Lomi, & Torlò, 2013). Research extending ERGMs to longitudinal data is promising, but it is only moving its first steps (Koskinen & Lomi, 2013).

In spite of these limitations, we think that the results we have presented clearly demonstrate the benefits of accounting for potential multilevel mechanisms when modeling social networks. For researches interested in social networks in organizations, the models for multilevel networks that we have discussed and illustrated provide a useful addition to the set of more general multilevel models currently adopted in organizational research.

## Appendix

### *Creating input files (data)*

In order to perform the analysis with MPNet (<http://sna.unimelb.edu.au/PNet>), the input data have to be prepared and saved in the correct format. A general specification consists of the three network files and a few attribute files at least. All the file are in text format.

#### *Network data*

A separate file has to be created for each network. The file consists in a square binary matrix for network **A** and **B**, and a rectangular binary matrix for network **X**.

#### *Actor data*

A separate attribute file has to be created for each set of actors and each type of attributes (binary, categorical, continuous).

### *Running the analysis*

Specifying and estimating MERGMs requires performing a set of steps. Once the data file have been uploaded into MPNet, the effects that are expected to affect the multilevel network structure have to be selected. Usually, models are estimated in order of increasing complexity. It is advisable to start with a very simple model, and make it more complex adding few effects in each run. First, a lower-level model is specified. Then, multilevel effects are added. After each run and before more complex models can be fitted, the model convergence has to be checked. In detail:

1. Import the input files.
2. Select which lower-effects to include in the model specification.
3. Start an estimation run.
4. Check the multicollinearity of effects in the output file.



5. Check the model convergence. A model is considered fully converging if the absolute values of the *t-ratios* for all the included effects are smaller than 0.1. To gain convergence, it is possible to fine-tune the MCMCML parameter values (i.e., number of subphases, multiplication factor, and maximum estimation runs can be increased).
6. Update the estimates.
7. Check the goodness of fit of the model, according to the procedure illustrated in the paper. Like in standard MCMCML estimation procedure, the sample size of the simulated networks to extract as well as the number of iterations have to be specified.
8. Include further effects and repeat the steps 3-7 until a successful model is obtained.

More details on these aspects are reported in the PNet and MPNet manuals.

#### *Additional points*

If one is interested in assessing the effect of shared – possibly multiple – affiliations to non-connected units on lower-level interaction within and between units (see, for example, Sosa, Gargiulo, & Rowles, 2014), the higher-level network need not be included. Cross-level configurations are not tested.

#### **Note**

1. In non-experimental studies based on sampling, ignoring nonindependence could result in: (1) too small an estimate of standard errors associated with model parameters and, as a consequence, the detection of an effect which is not significant (Type I error); (2) too little power of statistical tests and, as a consequence, a failure to detect an effect which is significant (Type II error)
- 2 For example, the tie  $b_{ij}$  can be included in either a reciprocal dyad with the tie  $b_{ji}$ , or a triangle with the ties  $b_{jh}$  and  $b_{ih}$ .
3. It is worth outlining that examining and treating multicollinearity offers only limited assistance in this context, because the statistics are correlated by default. As a rule of thumb, correlation lower than 0.8 in absolute value is considered acceptable.
4. Five consultants were also included in the list because of the direct and personal relations with the president-founder of the group and because of their crucial role in boat design. In the text we will refer to the 47 respondents generically as “managers” unless the distinction between “managers” and “consultants” is essential to the argument.

5. Our “bottom-up” approach to reconstructing the intraorganizational hierarchy between the subsidiary units has a high degree of nominal validity because all the relations of subordination flow from the corporate center (which is superordinate) to the subsidiaries. Our approach also allows us, however, to discover hierarchical relations between subsidiaries. See Figure 1.
6. The corresponding odds of one organizational member communicating to another colleague against not communicating decrease from  $[e^{-2.31}] = 0.099$  in Model 1 to  $[e^{-3.41}] = 0.033$  in Model 2 and  $[e^{-7.52}] = 0.001$  in Model 3.
7. The odds are respectively  $[e^{3.13}] = 22.87$  in Model 2 to  $[e^{2.62}] = 13.74$  in Model 3.
8. The parameter  $\lambda$  takes value 4, which corresponds to a highly skewed out-degree distribution. Thus, a small number of very active organizational members coexist with a majority of others who are likely to interact with few colleagues (Hunter, 2007; Hunter & Handcock, 2006).

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**Table 1.** Basic network descriptive statistics for the interpersonal network.



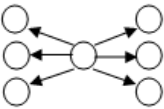
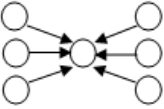
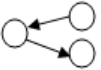
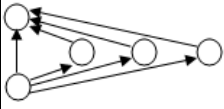
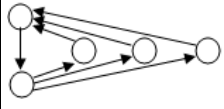
<b>Statistics</b>	<b>Values</b>
Density	0.08
Number of ties	164
Mean in-/out-degree	3.49
Standard deviation in-/out-degree	1.85 -- 2.65
Minimum in-/out-degree	0
Maximum in-/out-degree	6 -- 10
Number of reciprocated pairs	55

**Table 2.** Basic descriptive statistics for individual and unit covariates.

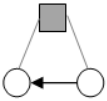
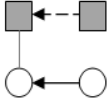
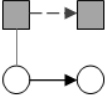
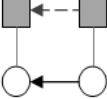
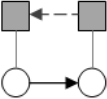
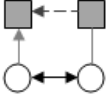
	<b>Relative Frequency</b>	<b>Mean (st.dev.)</b>
<b>Individual attributes</b>		
<b>Function</b> (i.e., membership in organizational function)		
CEO	12.8%	
Engineering	12.8%	
Finance	14.9%	
Marketing	8.5%	
Production	25.5%	
Others	25.5%	
<b>Gender</b>		
Female	14.9%	
Male	85.1%	
<b>Grade</b> (i.e., level of task performed)		
Clerk	12.8%	
Operations Manager	34.0%	
Manager	42.6%	
Consultant	10.6%	
<b>Nationality</b>		
Italian	87.2%	
Others	12.8%	
<b>Tenure</b> (i.e., number of years since an organizational member joined the group)		8.1 (7.5)
<b>Unit attributes</b>		
<b>Country</b> (i.e., country where a unit is based)		
Italy	66.6%	
US	16.7%	
International (i.e., no country based)	16.7%	
<b>Role</b>		
Corporate	16.7%	
Others	83.3%	
<b>Size</b> (i.e., number of members of each unit)		7.8 (4.8)




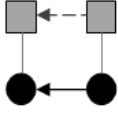
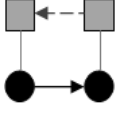
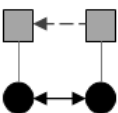
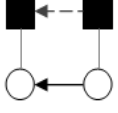
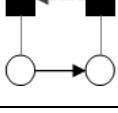
**Table 3.** ERGMs lower-level structural configurations. Circles denote individuals and black links denote (informal) communication relations between pairs of individuals.

Configuration	Representation	Qualitative interpretation
Density		Tendency of organizational members to communicate with colleagues
Reciprocity		Tendency of organizational members to communicate with reciprocating colleagues
Activity spread		Tendency of organizational members to be active – i.e., to communicate with many colleagues
Popularity spread		Tendency of organizational members to be popular – i.e., to be sought as communication partners by many colleagues
2-paths		Basic tendency of organizational members to communicate with and to be sought as communication partners by colleagues
Transitive closure		Tendency of organizational members to communicate with colleagues of colleagues
Cyclic closure		Tendency of organizational members to communicate with colleagues in small groups without any expectation of being

**Table 4.** MERGMs higher-level structural configurations. Circles denote individuals and squares denote organizational units (subsidiary units in our data). Solid black links denote (informal) communication relations between pairs of individuals, while dashed black links denote (hierarchical) subordination relations ties between pairs of units. Grey links (between circles and squares) denote affiliation ties of individuals to units (containment relations).

Configuration	Representation	Qualitative interpretation
Affiliation based closure		Tendency of organizational members to communicate with colleagues based on common membership in units
Cross-level in-degree assortativity		Tendency of popular organizational members in communication network to be affiliated to popular (i.e., hierarchically subordinate) units in interunit network
Cross-level out-degree assortativity		Tendency of active organizational members in the communication network to be affiliated to active (i.e., hierarchically superordinate) units in interunit network
Cross-level alignment entrainment		Tendency of organizational members to communicate with colleagues affiliated to units hierarchically subordinate to their unit
Cross-level alignment exchange		Tendency of organizational members to communicate with colleagues affiliated to units hierarchically superordinate to their unit
Cross-level alignment exchange reciprocal B		Tendency of organizational members to communicate with reciprocating colleagues affiliated to units with which a hierarchical relation exists

**Table 5.** ERGMs and MERGMs lower- and higher-level covariate configurations. Black denotes an individual or a unit with a relevant attribute.

Configuration	Representation	Qualitative interpretation
Covariate match		Tendency of organizational members to communicate with colleagues with the same value of a covariate
Cross-level alignment entrainment individual covariate match		Tendency of organizational members with a given value of a covariate to communicate with colleagues with the same level of the covariate and affiliated to units hierarchically subordinate to their unit
Cross-level alignment exchange individual covariate match		Tendency of organizational members with a given value of a covariate to communicate with colleagues with the same level of the covariate and affiliated to units hierarchically superordinate to their unit
Cross-level alignment exchange reciprocal B individual covariate match		Tendency of organizational members with a given value of a covariate to communicate with reciprocating colleagues with the same level of the covariate and affiliated to units with which a hierarchical relation exists
Cross-level alignment entrainment unit covariate match		Tendency of organizational members affiliated to units with a given value of a covariate to communicate with colleagues affiliated to units with the same level of the covariate and hierarchically subordinate to their unit
Cross-level alignment exchange unit covariate match		Tendency of organizational members affiliated to units with a given value of a covariate to communicate with colleagues affiliated to units with the same level of the covariate and hierarchically superordinate to their unit

**Table 6.** ERGMs and MERGMs estimates of interpersonal and interunit networks.

	<b>Model 1</b>	<b>Model 2</b>	<b>Model 3</b>
	<b>Tie independent</b>	<b>Lower-level</b>	<b>Multi-level</b>
	<b>model</b>	<b>network model</b>	<b>network model</b>
	<b>par. (st.dev.)</b>	<b>par. (st.dev.)</b>	<b>par. (st.dev.)</b>
<b>Lower-level effects</b>			
Density	-2.31 (0.21)*	-3.41 (0.44)*	-7.52 (1.19)*
Reciprocity		3.13 (0.46)*	2.62 (0.51)*
2-paths		-0.28 (0.07)*	-0.19 (0.07)*
Popularity spread ( $\lambda=4$ )		-0.11 (0.18)	-0.08 (0.23)
Activity spread ( $\lambda=4$ )		0.35 (0.15)*	0.50 (0.17)*
Transitive closure ( $\lambda=2$ )		1.28 (0.20)*	0.79 (0.21)*
Cyclic closure ( $\lambda=2$ )		-0.02 (0.19)	-0.16 (0.20)
Function match	0.24 (0.21)	0.14 (0.14)	0.38 (0.22)
Gender match	-0.77 (0.76)	-0.51 (0.57)	0.05 (0.81)
Grade match	0.53 (0.16)*	0.23 (0.09)*	0.03 (0.22)
Nationality match	0.12 (0.20)	-0.06 (0.14)	0.58 (0.34)
Tenure match	-0.03 (0.01)*	-0.02 (0.01)*	0.13 (0.17)
<b>Higher-level effects</b>			
Affiliation based closure			2.74 (0.67)*
Cross-level in-degree assortativity			1.17 (0.48)*
Cross-level out-degree assortativity			0.21 (0.17)
Cross-level alignment entrainment			0.50 (2.93)
Cross-level alignment exchange			2.76 (3.61)
Cross-level alignment exchange reciprocal B			2.14 (0.93)*
Alignment entrainment unit country match			-0.33 (0.92)
Alignment exchange unit country match			-1.58 (1.33)
Alignment entrainment unit role match			-0.44 (2.88)
Alignment exchange unit role match			-3.46 (3.67)
Alignment entrainment unit size match			-0.09 (0.23)
Alignment exchange unit size match			-0.20 (0.28)
Alignment entrainment organizational member function match			2.12 (0.95)*
Alignment exchange organizational member function match			1.90 (1.31)
Alignment exchange reciprocal B organizational member function match			-4.31 (1.97)*
Alignment entrainment organizational member grade match			-1.06 (1.13)
Alignment exchange organizational member grade match			1.46 (1.45)
Alignment exchange reciprocal B organizational member grade match			0.01 (2.18)

\* Indicates that the ratio of statistic to standard error is greater than 2 (Two-sided tests)

**Table 7.** Goodness of fit diagnostics for selected structural network properties.

Statistics		Model 1		Model 2		Model 3	
	Observed	Simulated mean (st.dev.)	t-ratio	Simulated mean (st.dev.)	t-ratio	Simulated mean (st.dev.)	t-ratio
St. dev. in-degree distribution	1.85	1.92 (0.21)	-0.34	1.84 (0.19)	0.05	1.85 (0.18)	-0.00
Skewness in-degree distribution	-0.20	0.45 (0.33)	-1.95	-0.01(0.29)	-0.66	0.01 (0.26)	-0.77
St. dev. out-degree distribution	2.65	1.92 (0.21)	3.46	2.50 (0.25)	0.61	2.55 (0.27)	0.38
Skewness out-degree distribution	0.69	0.42 (0.31)	0.86	0.25 (0.29)	1.52	0.44 (0.33)	0.74
GCC Transitive closure	0.49	0.08 (0.01)	29.27	0.46 (0.05)	0.81	0.50 (0.05)	-0.14
GCC Cyclic closure	0.42	0.08 (0.02)	16.91	0.40 (0.05)	0.37	0.44 (0.05)	-0.33